

FinTech Lending with LowTech Pricing*

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Abstract

FinTech lending—known for using big data and advanced technologies—promised to break away from the traditional credit scoring and pricing models. Using a comprehensive dataset of FinTech personal loans, our study shows that loan rates continue to rely heavily on conventional credit scores, including a 45% premium for nonprime borrowers. Other known default predictors are often neglected. Loan rates are not responsive to risk, with realized loan-level returns decreasing with risk. These patterns reflect rather simplistic and inefficient pricing. The pricing distortions result in substantial transfers from low-risk to high-risk loans.

Keywords: FinTech, Personal loans, Credit score, Nonprime borrowers, Market segmentation

JEL Classification: G21, G23, G50

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1 Introduction

Over the last decade, FinTech lending has become a popular source of funds for individuals and has drawn in immense investment from capital providers.¹ Compared to traditional lenders who use credit scores (e.g., FICO score) as the primary underwriting tool to screen applicants and price loans, FinTech lenders promise to bring improvement in underwriting by accessing new sources of data and applying advanced statistical techniques.² Indeed, increasing the efficiency of credit allocation and tightening the link between pricing and risk would improve the welfare of borrowers, especially underserved populations with weak credit scores. As summarized by U.S. House Representative Trey Hollingsworth:³

“We are finding people who may, by traditional standards, have challenging credit scores or challenging situations, but through new algorithms, new technology, and new capabilities, are saying they might be great credit risks for these type of products.”

FinTech lenders appear to be exactly where big data and statistical analysis can pose a significant competitive advantage relative to traditional lenders.⁴ It is an empirical question,

¹For example, in the \$138 billion unsecured personal loan market, the share of online loans increased from 22% to 49% over 2015–2019. Details can be found in a report by Experian: <https://www.stlouisfed.org/publications/regional-economist/second-quarter-2019/unsecured-personal-loans-fintech>.

²See, for example, Chris Lau, Why Hyper-Growth in AI Will Lift Upstart, February 7, 2022, available at <https://www.nasdaq.com/articles/why-hyper-growth-in-ai-will-lift-upstart>.

³See more discussions about FinTech lending in hearing testimony before the Subcommittee on Financial Institutions and Consumer Credit of U.S. House of Representatives Committee on Financial Services (January 30, 2018). For example, Nathaniel Hoopes, executive director of the Marketplace Lending Association, states “There is great evidence that partnerships between originating banks and marketplace lenders are delivering products to underserved communities, places where bank branches have closed and delivered products that are more affordable than the products that were available from traditional institutions and doing so by using advanced techniques that go beyond just looking at a traditional FICO score.”

⁴On the intrinsic margin, FinTech borrowers benefited from increased operational efficiency (Buchak, Matvos, Piskorski, and Seru, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019; Berg, Burg, Gombović, and Puri, 2020a). On the extrinsic margin, individuals with limited prior access to the traditional credit markets could be viable borrowers of FinTech credit (Jagtiani and Lemieux, 2019; Berg et al., 2020a; Dolson and Jagtiani, 2021; Di Maggio, Ratnadiwakara, and Carmichael, 2021; Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2022). Furthermore, FinTech lenders extend credit access to previously unserved or underserved populations (Hau, Huang, Shan, and Sheng, 2019; Agarwal, Kigabo, Minoiu, Presbitero, and Silva, 2021). They also substitute bank lending to riskier borrowers during the financial crisis of 2007–2009 (Tang, 2019; Balyuk, Berger, and Hackney, 2020; Chava, Ganduri, Paradkar, and Zhang, 2021; Di Maggio and Yao, 2021).

however, whether they indeed utilize all the information available to them in their pricing decisions. If this were the case, then the pricing of FinTech loans should better reflect borrowers' credit risk beyond credit scores. It is possible, however, that FinTech lenders face constraints preventing them from implementing risk-based pricing; for instance, their capital providers may rely on credit scores in their own underwriting and pricing decisions.

In this paper, we assess the ability of FinTech lenders to break away from traditional loan pricing decisions of unsecured personal loans. Our analysis indicates that the pricing of FinTech loans heavily relies on FICO scores, and strikingly ignores other well-known predictors of default. Of particular concern is the fact that loans with the same risk bear grossly different interest rates in the prime and nonprime market segments (as defined by FICO scores above and below 660). We estimate the pricing discrepancies in this market relative to counterfactual rates based on traditional lending. Our results show that borrowers in the nonprime segment of the market subsidize borrowers in the prime segment. Within segments, borrowers with good credit quality subsidize those with poor credit quality.

We use a unique dataset compiled by a data aggregator that contains most of the unsecured FinTech personal loans made in the U.S. throughout 2014–2020. The original dataset covers about 70% of FinTech unsecured personal loans in the U.S. over that period, originated via online platforms such as LendingClub, Upstart, and Avant. The data is used in real-time by institutional investors as well as by the lenders themselves. While these platforms always perform the borrower screening and loan pricing, they have access to different sources of capital, i.e., either their own or investors' capital (e.g., mutual funds and banks) via whole loan sales or securitization. Our data includes information about borrowers (e.g., credit score) and loans (e.g., contract terms and performance), but not applications, investor identity, and the sources of capital. The nature of the data allows us to study pricing decisions in FinTech lending and draw broad conclusions about the emerging industry.

Our main empirical finding is illustrated in Figure 1: the pricing of FinTech loans has not broken away from pricing based on traditional FICO scores. In both panels, the x -axis

presents borrowers' FICO score at origination, and the y -axis reflects a simple measure of ex-ante delinquency risk (discussed later in detail). This measure is based on observable characteristics at origination, excluding FICO score. Panel A presents a heat map of the average loan rate. The panel clearly shows that the main determinant of loan pricing is the traditional FICO score. At the same time, our ex-ante default measure based on other variables adds very little explanatory power to interest rates. Panel B presents the ex-post outcomes of loans, measured by the average delinquency rate. It shows that the FICO score and other known default predictors predict loan performance out-of-sample. Together, these charts paint a picture of a market in which prices are heavily determined by traditional FICO scores and are grossly insensitive to other readily-available information about future performance.

FinTech platforms' over-reliance on FICO scores in their pricing decisions has particular economic consequences regarding the existing segmentation of the personal credit market. Specifically, prime borrowers (those with FICO scores ≥ 660) generally have access to traditional unsecured and secured credit. Conversely, nonprime borrowers (with FICO scores < 660) do not have access to such credit, and therefore, FinTech lending presented a much-needed opportunity for them. We estimate that nonprime borrowers pay significantly higher interest rates by 7.33 percentage points (pp) than prime borrowers with the same default risk. The magnitude of the interest rate gap is robust to the estimation method, e.g., regression discontinuity design (RDD) or an out-of-sample default propensity score model. Importantly, the rate gap between the market segments does not change over time, suggesting a little impact on lender competition or learning. We explore other explanations for the rate gap, such as expected prepayment risk or unobserved risk that may manifest during a crisis. However, none appears to justify the rate jump.

We conjecture that the prime/nonprime rate gap reflects institutional factors to which FinTech lenders are exposed, making it difficult to break away from traditional pricing models. For example, due to regulatory constraints, banks must avoid originating and investing

in nonprime loans and are thus mostly absent in the segment. As a result, nonprime lending can only be funded by nonbank capital through equity offerings, loans, or securitization, and thus, FinTech lenders face much less competition from banks. In contrast, in the prime segment of the market, FinTech lenders are exposed to greater competition from banks. Due to banks' access to low-cost deposit funding, equilibrium loan rates are substantially lower.

In addition to the substantial rate gap for nonprime borrowers, rates are mostly insensitive to other known predictors of default. The under-sensitivity leads to the curious outcome that loan-level returns decline with risk. While one could attribute FinTech's pricing focus on FICO to industry factors, it is difficult to reconcile the lack of pricing sensitivity to risk with anything but a lack of sophistication. FinTech's new technologies may allow them to underwrite loans to previously underserved populations, but these technologies have not led to risk-based pricing.

Given the estimated gaps in the pricing of FinTech loans and the insensitivity of rates to risk, we set out to estimate the welfare consequences of these pricing distortions. To achieve this goal, we need *a counterfactual rate* that would have been charged by an *ideal* lender that fully implements risk-based pricing had the lender originated the loans. A necessary ingredient is the expected return that lenders anticipate to receive on their investment. Empirically, loans in the segment of the lowest default likelihood appear to persistently generate constant return to their lenders (most likely, banks), of about 5%. We assume that riskier loans should be priced such that they generate at least this rate. Therefore, by anchoring the expected return at that level and then using our out-of-sample delinquency risk measure, we can estimate a counterfactual rate for the remaining loans in the prime segment as well as for all loans in the nonprime segment. The difference between the actual rate and the counterfactual rate is the implied premium or discount attributable to mispricing, either due to market segmentation or miscalculated risk.

Using our estimated rate differentials, our analysis reveals economically significant cross-subsidization or mispricing across- and within-market segments. Specifically, nonprime bor-

rowers subsidize prime borrowers, on average, and low-risk borrowers subsidize riskier borrowers within segments. Over 83% of the nonprime borrowers overpay relative to the counterfactual rates. On average, all nonprime loans in our sample overpay by 4.3 pp and those with similar risk to prime loans overpay by about 8 pp (30% of their average rate). In contrast, most prime borrowers are either priced adequately (by design) or underpay relative to their counterfactual rates. The average overpayment by nonprime loans with similar risk to prime loans is about \$490 in the first year and \$980 over their loan terms, while prime loans with similar risk receive \$109 in the first year and \$218 through maturity per loan.⁵

Overall, our analysis indicates that FinTech loan pricing is surprisingly simplistic or “LowTech”: It relies heavily on borrowers’ credit scores while neglecting alternative data sources or other known risk factors. Our findings indicate that some of the longstanding pricing regularities in traditional lending markets (e.g., [Keys, Mukherjee, Seru, and Vig, 2010](#); [Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2018](#); [Argyle, Nadauld, and Palmer, 2020](#)) persist in the digital age and have not improved over the course of our sample period. We discuss the frictions that could generate these patterns and assess their implications for borrowers. As a result, nonprime individuals, who previously had little access to unsecured credit, have gained access, but most appear to overpay relative to their level of credit risk.

Our findings offer a silver lining for the FinTech industry. While loan pricing appears rather simplistic by the time our sample ends, there is significant scope for effortless improvement in the efficiency of loan pricing. Such an improvement would increase the access to fairly-priced credit to households, especially those underserved, and provide a fair risk-adjusted return to investors. Moving in this direction will likely enhance capital allocation across borrowers and increase consumer welfare.

The remainder of the article is organized as follows. Section [2](#) describes the data and

⁵[Hurst, Keys, Seru, and Vavra \(2016\)](#) document cross-subsidization of mortgage borrowers across regions. The distortion or mispricing results in transfers similar in magnitude to our estimates here (−\$580 to +\$780), albeit the size of mortgage are an order of magnitude larger than FinTech loans, and their duration is materially longer.

the sample construction and provides summary statistics. Section 3 presents results on the pricing discontinuity around the 660 FICO cutoff using RDD and controlling for credit and market risk. We then propose several institutional features of the consumer credit market that can explain the pricing discontinuity. Section 4 assesses the relationship between predicted risk and interest rates within different market segments. We conclude that FinTech platforms’ pricing strategy is rather simplistic and inefficient. Section 5 estimates how loan rates should have been priced under counterfactual rates for individual loans and associated cross-transfers. Finally, Section 6 concludes.

2 Data and Summary Statistics

2.1 Data

The initial sample includes 7.4 million loans originated between January 2014 and July 2020 by seven of the largest online lenders and available through a leading FinTech loan aggregator. This dataset encompasses the vast majority of all FinTech personal loans made online—roughly 70% in terms of volume.⁶ All loans are originated via online platforms such as LendingClub, Upstart, and Avant, which provide screening, pricing, and tracking services. Loans are funded either by lenders’ own capital or investors’ capital (typically institutional investors).

For each loan, we observe several key borrower characteristics available to lenders at the time of underwriting and pricing, including FICO score, annual income, and credit utilization ratio, loan purpose (e.g., debt consolidation), and homeownership status. We also observe the loan terms, including amount, maturity, scheduled payments, and annual interest rate. Last, the dataset includes performance information, including month-by-month principal and interest payments. In addition, the dataset includes delinquency status by month: current,

⁶This estimate is based on quarterly loan volumes aggregated in the U.S. Fintech Market Report by S&P Global Market Intelligence in February 2021.

delinquent, defaulted, and charge off. In the event of a charge off, actual recoveries and losses are reported.⁷

2.2 Sample

Several filters are applied to the data to ensure that the analysis is not affected by idiosyncrasies in data reporting. We first address our inability to verify whether reported interest rates include upfront fees or exclude them. One could back out the APR if given the gross loan amount, origination fees, and scheduled loan payments. However, in the data, it is unclear whether loan amounts are gross or net of fees; for many observations, origination fees are missing. Therefore, we restrict the sample to loans with amounts that are multiples of \$500 or \$1,000, as these round loan amounts are likely to exclude fees. This filter reduces the sample by 1.7 million loans. An additional 100,000 loans are dropped when we require the reported interest rate to equal the interest rate implied by the loan terms.⁸

We further filter the sample based on loan maturity and apparent censoring of FICO scores. We limit the sample to loans with maturities of 36 months—the most popular term—which reduces our sample by 1.6 million. Inspecting the data, it appears that some borrowers have precise FICO scores while others are censored. This censoring means that in a histogram of FICO scores, we observe spikes at FICO scores ending in 2 or 7 and every other 9, suggesting that some lenders report all borrowers within a range of FICO scores using a single value (e.g., 652 for 650–654). For FICO scores ending in 2 or 7, we assume that these correspond to a five-point bin average and leave them in the data set. We exclude those borrowers censored at every 20-point FICO ending in 9 because our identification requires

⁷“Recoveries” refers to the total cash payment that the lender receives when the loan is sold off to other investors or debt collection agencies. This variable is critical in computing the return to the investor, and in many cases, it is an unobserved variable that limits the ability to make precise calculations. For example, [De Roure, Pelizzon, and Thakor \(2021\)](#) estimate returns, but they have to assume different recovery rates and verify that results are insensitive to these rates. [Di Maggio et al. \(2021\)](#) calculate realized returns to the lender but assume full repayment after 12 months. Due to our long time series, we can calculate returns to matured loans.

⁸They could differ if the reported rate were an all-in APR, but the loan amount was reported gross of fees.

us to compare loans with FICO bins in the 655–659 and 660–654 ranges. Doing so reduces our sample by an additional 765,000 observations.

Last, we drop loans for which any variables needed in regressions are missing, including loan amount, payment, default, state, and origination time. Unless otherwise noted, we also drop any loans originated after July 2019 to give us a performance window of at least 12 months.

These restrictions result in a sample of 2.3 million loans. Our results are largely insensitive to all of these restrictions, but we choose to be conservative to alleviate any concerns that may arise from the inclusion of these observations.⁹

We calculate the ex-post realized returns for each loan as the internal rate of return (IRR) using all the previously described cash flows.¹⁰ By focusing on loans with a single term (36 months), we avoid comparability issues arising from comparing cash flows with different terms.¹¹

2.3 Summary Statistics

Table 1 provides summary statistics for loan terms, borrower characteristics, and loan performance. The average interest rate and loan size on these unsecured loans are 16.3% and \$11,898, respectively. Borrowers have a median income of \$62,500, which is very similar to the national median household income in 2018 of \$63,179.¹² The average (median) FICO score is slightly above prime at 684 (677). The average revolving credit utilization of 53% is

⁹To illustrate the differences between the final sample and the entire dataset, see interest rates by FICO depicted in Figure A.1 in the Appendix. The filtered sample has a slightly higher jump around the non-prime/prime cutoff than the unfiltered data, by about 2 pp.

¹⁰To provide a more concrete example of how returns are calculated, consider a \$10,000 loan with a 20% interest rate that requires equal payments of \$371 for 36 months. In this example, the IRR would equal the interest rate of 20%. However, if the payments stopped after ten months and the loan was charged off in month 13, we include the monthly recoveries as one of the cash flows. Hence, if recoveries in month 13 are \$3,000, then the IRR would be -57% . Last, we use the IRR to compute the effective annual interest rate of the loan. We do so to ensure that annualized returns are not below -100% .

¹¹E.g., loans with the same origination date and different maturities may be exposed to different economic shocks.

¹²See <https://www.census.gov/library/stories/2019/09/us-median-household-income-not-significantly-different-from-2017.html>.

above the average for households in the U.S. of 42%–45%.¹³ This relatively high utilization rate is expected, given that these loans are predominantly made to individuals who intend to consolidate their debt or pay off high credit card balances. Almost three in four borrowers (76%) take out a FinTech loan for this purpose, while other cited purposes are other (11%), home improvement (7%), and medical expenses (1%).

3 The Prime/Nonprime Rate Gap

Does FinTech lending break away from traditional lending that focuses heavily on FICO scores? In this section, we estimate a substantial pricing gap between otherwise similar borrowers that are categorized as prime or nonprime borrowers based on FICO scores. We then discuss institutional factors that could lead to an equilibrium where rates differ substantially for these two market segments.

3.1 RDD Regressions

Panel (a) of Figure 2 plots point estimates and confidence intervals from regressions of interest rates on FICO score bins while controlling for origination year-month fixed effects. The five-point FICO bins begin at FICO 600 and end at 720, with an increment of five points (e.g., 650–654). The estimated coefficients for each FICO bin represent the average level of these variables for all loans contained in the bin. Panel (a) shows a striking jump at FICO 660—the threshold for prime borrower status, with the average interest rate on the loans shifting from 16.8% in the 660–664 FICO bin to about 25% in the 655–659 FICO bin, increasing by more than 8 pp. In contrast, there is no discontinuity across FICO bins above 660 and much smaller jumps among bins below 660. Figure A.2 in the Appendix plots estimates from regressions of interest rates on other variables using similar specifications. While Panel (a) shows discontinuously smaller loan sizes for nonprime borrowers, Panels (b)

¹³See “revolvers” utilization in reports by the American Bankers Association. See <https://www.aba.com/news-research/research-analysis/credit-card-market-monitor/>.

and (c) show no discontinuity in either income or monthly payment in FICO scores. Thus, the discontinuity in pricing is not simultaneously a change in FICO and some other innate characteristic of the borrower.

Panel (b) of Figure 2 shows a moderate jump in the delinquency rate at FICO 660, while continuous patterns generally persist elsewhere. This discontinuity in performance is not entirely unanticipated, given the significant price jump. Adverse selection and moral hazard might induce both the selection of borrower types (on unobservable characteristics) and subsequent changes in repayment behavior. Both of these effects result from higher interest rates and not because there is anything uniquely risky about borrowers who happen to be at FICO 659 at origination instead of 660. What is surprising, however, is that despite having higher rates of delinquency, these nonprime borrowers consistently deliver returns to the lender that are substantially higher (6.3 pp or a 266% increase) than prime borrowers, as seen in Panel (c) of Figure 2.

Exploiting the discontinuity, we next use an RDD approach to quantify the magnitude of the jump in interest rates and ex-post performance at FICO 660. This approach allows us to test the sensitivity in this jump to the inclusion of other fixed effects and covariates within a narrow window. For example, loan amounts also change at the cutoff and could potentially explain some of the disparities if lower loan amounts are associated with higher loan rates.

To identify the differences in outcomes (e.g., rate), r , between the otherwise similar prime and nonprime borrowers, we estimate the following model:

$$r_{it} = \beta_1 \cdot I(FICO_{it} < 660) + \beta_2 \cdot I(FICO_{it} < 660) \cdot (FICO_{it} - 660) + \beta_3 \cdot (FICO_{it} - 660) + \theta_{it} + \gamma_i + \mu_t + \nu_{t,s} + \epsilon_{it}, \quad (1)$$

where $FICO_{it} \in [660 - h, 660 + h]$. The variable $I(FICO_{it} < 660)$ is an indicator equal to one if the FICO score is less than 660 and zero otherwise. The primary coefficient of interest,

β_1 , is the estimated jump in the outcome for individuals below prime. The bandwidth h identifies the window around the cutoff for which observations are required to fall to be included in the estimation. While not essential, especially in a very localized window around the threshold, the second and third terms in the equation allow the slope to differ above and below 660. We also include the loan amount (θ_{it}) and fixed effects for origination month (μ_t), state (γ_i), and state-by-year ($\nu_{t,s}$).

Table 2 reports the results of the RDD regressions. Columns (1)–(3) show that interest rates jump by 8.6–9.4 pp for nonprime borrowers, compared to similar prime borrowers within a very narrow window. Magnitudes differ by less than one pp when the bandwidth around FICO 660 goes from 40 in Column (1) to 5 in Column (3) which excludes FICO controls, given the tight window around the cutoff.¹⁴ Columns (4)–(6) indicate that delinquency rates jump by 4.4–4.9 pp for nonprime borrowers. This is a relatively large increase from an average delinquency rate of 8.2% for prime borrowers. The magnitude of the estimated pricing gap is economically large.

We note, however, two important caveats to the RDD analysis. First, RDD can only be used to compare loans within a narrow band near the FICO cutoff, making it hard to generalize to a larger sample. Second, we cannot decompose the estimated price jump into what can be justified by expected risk and what cannot since lenders may price expected risk differently.

3.2 Interest Rate Gap Unrelated to Credit Risk

To address the caveats of the RDD analysis, in this subsection, we estimate a model of delinquency risk and use the predicted delinquency rate to assess the interest rate gap unrelated to ex-ante risk.

¹⁴Furthermore, because many loans have FICO scores that are censored at 2s and 7s, the inclusion of RDD controls may be largely influenced by this bunching.

3.2.1 Assessing Credit Risk

We estimate a logit model that regresses the delinquency indicator on borrower and loan characteristics in the following specification:

$$I(DLQ)_{it} = \beta \cdot X_{it} + \epsilon_{it}, \quad (2)$$

where $I(DLQ)_{it}$ is an indicator of whether the loan, taken out by the borrower i , becomes delinquent in the first 12 months after origination date t , and X_{it} is a set of borrower and loan attributes at origination date, including 20-point FICO bins, \$5,000-increment income bins, \$1,000-increment loan amount bins, and indicators for the loan purpose as well as the age of the oldest credit, revolving utilization, and the number of credit inquiries in the last six months from the credit bureau data. We also include $\Delta FICO$, which is the difference between the FICO bin and the actual FICO score, to account for FICO variation within bins. To obtain an ex-ante measure of risk for each loan originated in month t , we run rolling regressions using loans originated between months $t - 36$ and $t - 12$. The 12-month gap between estimation and prediction ensures that we only use the information available at origination.

Figure 3 plots selected coefficients for four regressions in the time series, while others are plotted in Figure A.3 in the Appendix. The coefficients are relatively stationary across the four year-months that are plotted.¹⁵ The two panels show that risk decreases monotonically with FICO and income, as anticipated. To save space, loan amount bins, loan purpose, and other credit bureau coefficients are plotted in the Appendix.

We evaluate the performance of the model in two ways. The first is to look at the area under the curve (AUC), a commonly used measure for prediction accuracy. An AUC of 50% implies that the model does no better than random chance, while 100% has perfect predictive capabilities. It is generally accepted that 70% is considered good, especially

¹⁵The period 2017m1 refers to the regression that predicts loan delinquency for January 2017. This regression includes data from January 2014 to December 2015.

in information-scarce environments. The average AUC in our regressions is close to that benchmark at 66.52%, which squares with other unsecured debt models documented in the literature.¹⁶ The second approach is to plot the average predicted delinquency $I(\widehat{DLQ})_{i,t}$ against realized delinquency separately for the prime and nonprime markets. If the model performs well, we expect to see little difference in performance between the two markets and for the slopes to line up close to the 45-degree line. We plot the average delinquency for 50 predicted delinquency bins separately for prime and nonprime loans in Figure 4, Panel (a). The standard errors between the two markets are mostly overlaid in the region where prime and nonprime loans have similar ex-ante risks. The figure confirms that realized delinquency aligns well with predicted delinquency (lies on the 45-degree line). There is also a consistent overlap between the two markets, which we will use in later tests. We will refer to this region as the “overlapping region” of risk.

Panel (b) of Figure 4 shows the relation between ex-ante risk and default for the subset of loans that have reached maturity by July 2020. The results confirm that predicted delinquency and realized default are closely related to this sample. Since default can happen at any time during the life of the loan, it is not surprising that default is higher than 12-month delinquency for any level of predicted delinquency. Surprisingly, however, prime borrowers tend to default at higher rates than nonprime borrowers for similar levels of ex-ante delinquency risk.

3.2.2 Estimating the Interest Rate Gap While Controlling For Credit Risk

Using a reliable measure of ex-ante risk, we compare the pricing of loans with similar risks. The exercise is relatively straightforward. We plot average interest rates over the predicted delinquency rate (in bins) separately for prime and nonprime borrowers in Figure 5, Panel (a). The difference in rates between the two is statistically and economically significant. This gap is plotted in Panel (b) for the overlapping region where we can comfortably compare

¹⁶For example, [Berg et al. \(2020a\)](#) find the AUC to be 68.3% using only credit bureau information in their data, and [Berg, Puri, and Rocholl \(2020b\)](#) calculate an AUC of 66.6% using data from a German bank.

loans with similar risk, as opposed to the far left or far right region, where we only see loans in one of the two segments. On average, rates for nonprime loans are about 10 pp higher than those for similar-risk prime borrowers, which is very similar to what we found in RDD regressions. The gap stays mostly the same over time and may even get a little bigger, which suggests that lenders do not learn much and that competition is not likely to close this gap.

By focusing on loans in the overlapping region, this ex-ante risk measure allows us to compare borrowers who may be far from the FICO 660 cutoff but with similar credit risk, which makes our findings more generalized than the RDD analysis. In other words, the overlapping region includes 848,000 borrowers, whereas the 10-point window around 660 includes only 213,000 borrowers. We make the measurement even more precise by regressing interest rates on the nonprime loan indicator while controlling for loan size and predicted delinquency risk, either as a continuous or a categorical variable, as follows.

$$r_{it} = \beta_1 \cdot I(FICO_{it} < 660) + \beta_2 \cdot I(\widehat{DLQ})_{it} + \theta_{it} + \mu_t + \epsilon_{it}, \quad (3)$$

where $I(\widehat{DLQ})_{it}$ is the ex-ante predicted risk obtained from rolling regressions specified in Equation (2); θ_{it} is the loan amount; μ_t is the origination time fixed effects. Table 3 presents the analysis. Our baseline specification is in Column (1) where we control for year-month fixed effects, loan amount and $I(\widehat{DLQ})_{it}$ as a continuous variable. Column (2) controls $I(\widehat{DLQ})_{it}$ as categorical variable and Column (3) adopts the same specification as in Column (1) but based on only loans with FICO score 20 points above and below the 660 cutoff. Results show that the rate gap between the two segments ranges from 6.22 to 7.33 pp and is statistically significant at the 1% level.

3.3 Controlling for Other Risk

In addition to credit risk, lenders may charge higher interest rates on loans with higher prepayment risk, which can result in the loss of revenue for lenders due to reinvestment risk

and thus justify higher rates on these loans. In Table 4, we present the analysis using as the dependent variable a prepayment indicator variable that equals 100 if the loan is prepaid before the maturity date and 0 otherwise. Columns (1)-(3) adopt similar specifications as in Table 3 where we control for predicted delinquency risk, loan amount and year-month fixed effects. Results are similar across different specifications. Column (1) suggests that nonprime loans are 2.85 pp more likely to be prepaid before maturity than prime loans of comparable risk and size, representing 7.3% of the average prepayment rate (39.02%).

To account for the difference in prepayment risk between nonprime and prime loans, we obtain the component of the expected prepayment risk that is orthogonal to the expected credit risk. We include it as an additional control in Equation (3). Results are reported in Columns (4)-(6) of Table 4. They show that the estimated rate gap between nonprime and prime segments is still 7.33 pp using our baseline specification in Column (4), which is identical to the magnitude found in Table 3, suggesting that estimated rate gap is unrelated to prepayment risk as well.

Magnitude of the Rate Gap Using the estimates from Column (4) in Table 4, the estimated rate gap of 7.33 pp is a 45% premium over the average rate for prime loans (15.45%) in the overlapping region. The gap accounts for 28% of the average rate for nonprime loans (26.45%) in the sample. With an average loan amount of \$5,344, these borrowers pay \$392 ($= 5344 \times 7.33\%$) in interest payments during the first year of the loan more than they would in the absence of the rate premium. The overpayment would be \$784 during the entire term assuming that expected duration is 2 years for a 3-year loan, equivalent to a week’s gross pay for someone making \$42,000 a year.

3.4 Performance During COVID-19

The performance of loans in our sample is updated through July 2020, including several months during the COVID-19 period. If nonprime borrowers were riskier than prime

borrowers based on unobservable characteristics, these factors would manifest when facing an unanticipated shock such as COVID, resulting in much worse performance for nonprime borrowers. To test the difference in performance during a crisis, we focus on the repayment behavior of FinTech loans before and during the COVID-19 crisis period, i.e., from October 2019 through July 2020. Specifically, our analysis includes loans that remain outstanding as of December 2019 and have predicted delinquency between 6.7% and 13.2% (the overlapping region).

Panel (a) of Table A.1 in the Appendix presents summary statistics of the panel data sample. It shows that loans in the nonprime sample have slightly higher ex-ante delinquency risk $I(\widehat{Delinquency})$ than those in the prime sample, primarily due to compositional differences. Their loan size is also much smaller. Following the onset of the COVID-19 pandemic, the delinquency rate of loans in both samples increased sharply to a very similar level, near 13%. We estimate the OLS regression in the following difference-in-difference (DID) specification based on the panel data:

$$I(DLQ)_{i,t} = \beta \cdot I(FICO_i < 660) \cdot I(COVID_t) + \gamma_i + \gamma_t + \theta_{i,t} + \epsilon_{i,t}, \quad (4)$$

where $I(DLQ)_{i,t}$ indicates whether the loan is delinquent at calendar time t ; $I(FICO_i < 660)$ indicates whether the loan is a nonprime loan; $I(COVID_t)$ is an indicator that equals 1 for months since March 2020, and 0 otherwise. As in a standard DID specification, we control for individual (γ_i) and time (γ_t) fixed effects. Hence, β captures the change in loan performance within-borrower before and after the onset of COVID-19. We also implement more stringent specifications by controlling for state \times time, origination date (t_0) \times time, and our predicted delinquency measure \times time fixed effects ($\theta_{i,t}$). These extra steps make sure that we only compare the performance of loans within the same state and same month of origination that have the same ex-ante risk level.

Table 5 presents the results. Column (1) reports the standard DID results, and the

other columns report the results with additional controls. Column (1) shows that nonprime loans perform slightly better during the crisis, with a 0.43 pp lower delinquency rate after March 2020 compared to prime loans during that same period and nonprime loans before the pandemic. In Column (2), where we control for ex-ante delinquency, the difference in performance is much more pronounced, with nonprime borrowers having a 2.08 pp lower delinquency rate compared with prime borrowers with similar ex-ante risk during COVID-19 as well as nonprime loans before the onset of the pandemic. The difference widens slightly in Column (3), where we control for predicted delinquency, state, and origination time. Following the onset of COVID-19, nonprime borrowers exhibited relatively better loan performance by 2.24 pp compared with prime loans that had similar ex-ante risk in the same state and same origination month during COVID-19, as well as nonprime loans before COVID-19. The magnitude is economically meaningful, as a raw decrease in delinquency of this size would have meant a 19.3% improvement from the pre-COVID-19 level.

These results show that nonprime loans had lower rates of delinquency during the COVID-19 period than similar prime loans before the COVID period. When we compare the performance of loans with similar ex-ante risk, the relative over-performance of nonprime loans is even more pronounced. The results suggest that nonprime loans do not have a significantly higher unobservable risk that would manifest when unanticipated shocks occur.

3.5 Why Does the Pricing Discontinuity Exist and Persist?

Why do lenders persistently charge different rates for loans around the 660 FICO cutoff with similar risks? In this subsection, we offer several explanations based on institutional features of the consumer credit market.

3.5.1 Limited Competition in the Nonprime Segment

During and after the global financial crisis, lending by large banks to small businesses and nonprime borrowers fell sharply and has not fully recovered ([Chen, Hanson, and Stein](#),

2017; Buchak et al., 2018). To provide direct evidence of limited bank credit supply in the nonprime segment, we hand-collect the minimum FICO requirements disclosed by banks and FinTech lenders online.¹⁷ We start by identifying the 15 largest banks in the U.S. by asset size. We restrict our list to those offering unsecured personal loans. Among the nine that offer this type of loan, we first search on the bank website for minimum qualifications and, if unavailable, then search on NerdWallet, WalletHub, or Bankrate. Only one (PNC Bank) of these nine had no qualifications listed anywhere. We report the other eight in boldface font in Table 6. In addition to the largest banks, we also include the minimum FICO score requirements reported for other prominent bank lenders like American Express, Discover, Barclays, and USAA. These banks appear to be significant players in the personal loan space.

Next, we conduct a similar search among FinTech lenders. These online lenders, including the seven largest ones reported in boldface font, are shown in the last row of Table 6.¹⁸ The contrast in lending requirements is stark between banks and non-banks. Online lenders often accept people with credit scores below 660, but none of the banks on this list do. The lack of bank lending to nonprime borrowers, corroborated by others in the literature,¹⁹ leads to limited competition and higher market power for FinTech lenders in the nonprime segment. This bifurcated market may explain part of the puzzle in disjointed rates at the prime cutoff. FinTech platforms that lend below prime do not have to compete with big banks and can more easily take advantage of borrowers, whereas in the prime space they have to compete with bank lending.

¹⁷Banks often post credit requirements on their websites. Personal finance websites like WalletHub, NerdWallet, and Bankrate summarize the loan products each lender offers and often list these requirements to help people decide where to apply for loans. For examples of how these websites display personal loan information, see <https://wallethub.com/best-banks-for-personal-loans> and <https://www.nerdwallet.com/best/loans/personal-loans/best-personal-loans>.

¹⁸Avant, Best Egg, LendingClub, LendingPoint, Prosper, SoFi, and Upstart are identified as the most prominent lenders according to the U.S. FinTech Market Report produced by S&P Global Market Intelligence in February 2021. For an older version of this report available without a specific request, see the 2017 version: https://pages.marketintelligence.spglobal.com/rs/565-BD0-100/images/DigitalLending_Public_Web.pdf.

¹⁹See, for example, the rejection rate for borrowers by FICO score among large banks in Di Maggio et al. (2021).

3.5.2 Regulatory Requirements

In exploring factors that contribute to the rise of shadow banks following the global financial crisis, [Buchak et al. \(2018\)](#) use data on the mortgage market to show that two forces, regulatory differences and technological advantages, explain the simultaneous decline of banks and dramatic growth among FinTech lenders. In particular, the Dodd-Frank Act’s changes to regulatory capital requirements and the restructuring of the financial regulatory framework have led to a big drop in bank lending.

In addition, banks must follow clear and strict rules when originating nonprime loans. For example, rules for nonprime lending (defined by borrowers below the 660 FICO cutoff) are spelled out in the FDIC Risk Management Manual for Examination Policies:²⁰ “Non-prime lending should only be conducted by institutions that have a clear understanding of the business and its inherent risks and have determined these risks to be acceptable and controllable given the institution’s staff, financial condition, size, and level of capital support. In addition, nonprime lending should only be conducted within a comprehensive lending program that employs strong risk management practices to identify, measure, monitor, and control the elevated risks inherent in this activity.” Basel III regulations are another example of how rules can raise the cost of loans to borrowers with impaired credit. In particular, the rule says banks must set aside more capital for riskier loans, with loan riskiness measured by external credit ratings such as FICO. Lower ratings are linked to lower credit scores, so it costs banks more to make and keep these loans on their balance sheets.

Even though FinTech companies do not have to pay for or follow these costs and rules directly, they can still be affected by them in two ways. One is the wholesale funding channel, which shadow banks and FinTech lenders use to get money from banks or other investors with higher regulatory costs. For example, several FinTech lending platforms, like Prosper, also make traditional direct-to-consumer loans through WebBank, an FDIC-insured, state-

²⁰See more details about the 660 FICO cutoff at https://www.fdic.gov/regulations/safety/manual/manual_examinations_full.pdf.

chartered industrial bank that has to follow some rules. The second way FinTech lenders can replace banks is by competing with them in the market for loans that banks make to other borrowers.²¹ If competing banks charge higher rates on nonprime loans due to higher regulatory costs, then FinTech lenders can also charge higher rates and remain competitive in this segment. In this case, bank rates on nonprime loans could become a pricing benchmark for FinTech lenders. [Jiang \(2019\)](#) uses mortgage data to demonstrate the two channels. Through both channels, there should be a hefty interest rate gap between nonprime and prime segments.

3.5.3 Funding Costs and Cross-Subsidization

FinTech lenders differ considerably from banks on several critical dimensions, including how they obtain funding and the regulatory environments in which they operate. Banks mostly depend on low-cost deposits insured by the government and are not tied to the risk of how banks lend money. In contrast, FinTech firms have to raise funds from wholesale funding or captive markets at a higher cost that compensates for the risk of their assets. In other words, FinTech platforms tend to charge higher rates that vary with risk in both prime and nonprime market segments. On the other hand, for FinTech firms to compete with banks in the prime segment, they cannot charge competitively high rates and thus have to cross-subsidize the rates on prime loans using a premium extracted from the nonprime segment. This sector structure helps explain in part why the cost of credit in our sample of FinTech loans is so high, especially for nonprime loans, and why one segment subsidizes the other.

²¹Our sample contains unsecured personal loans exclusively screened by FinTech platforms, whose investors include both banks and nonbanks. We do not have data on loans directly originated by banks.

4 Within-Segment Pricing and Loan Returns

The previous section showed that FinTech pricing continues to be dictated by FICO scores with an especially significant average pricing gap between prime and nonprime loans. The results are not justified by underlying risk, suggesting large deviations from risk-based pricing at the market segment level. In this section, we explore possible differences in the pricing-risk slope through which risk is priced in order to assess the efficiency of FinTech pricing within each segment. A steeper positive slope indicates higher sensitivity of interest rates to changes in risk. We also test the sensitivity of loan-level returns to risk to assess whether risk is adequately priced.

4.1 Relationship Between Expected Risk and Rates

To begin our analysis, we estimate the relationship between predicted risk and interest rates for four different market segments:

$$r_{it}^s = \beta_0^s + \beta_1^s \cdot I(\widehat{DLQ})_{it}^s + \mu_t^s + \epsilon_{it}^s, \quad (5)$$

where r_{it}^s , $I(\widehat{DLQ})_{it}^s$ and μ_t^s are defined the same as in Equation (2) except with a superscript s that is indexed to prime or nonprime loans. We also estimate Equation (5) using only those in the overlapping region, which enable us to compare the pricing of nonprime and nonprime loans with a similar risk and have an expected delinquency rates between 6% and 13%. Results are reported in Panel A of Table 7. Columns (1) and (2) are based on all nonprime and prime loans, respectively; Columns (3) and (4) are based on nonprime and prime loans in the overlapping region, respectively; Column (5) estimates a difference-in-differences (DID) specification by including the interaction of $I(\widehat{DLQ})_{it}^s$ and nonprime dummy and using both

prime and nonprime loans in the overlapping region.²² Finally, Column (6) estimates the relationship between price and risk for safe prime loans that we will later use in calibrating counterfactual rates.

The results highlight three important facts. First, consistent with results in Section 3, average rates in the nonprime market, captured by the coefficient on the nonprime indicator in Column (5), are significantly higher than those in the prime market by 13.98 pp. The estimated gap is higher than 7.33 pp in Table 4 because here we control for the interaction of nonprime dummy and predicted delinquency rate. Second, FinTech loan rates in the prime market are much more responsive to expected risk than those in the nonprime segment. Columns (1) and (3) show that a one-pp increase in the predicted delinquency rate raises the prime loan rate by 89.36 bp and 60.92 bp, respectively, compared to only 22.37 bp in Column (2) and 25.78 bp in Column (4) for the nonprime loans, respectively. This finding is further confirmed by the coefficient on the interaction term of the predicted delinquency rate and the nonprime indicator of -33.81 (significant at the 1% level) in Column (5), suggesting that a one-pp increase in the predicted delinquency rate raises the nonprime loan rate by 33.81 bp or 56% less relative to prime loans.

Third, loans in the overlapping and non-overlapping markets within the prime and nonprime markets are also priced differently. In general, the pricing slope is steeper for loans with lower risk and decreases along the risk spectrum of the loans, i.e., from non-overlapping prime (the least risky) \rightarrow overlapping prime \rightarrow overlapping nonprime \rightarrow non-overlapping nonprime loans (the most risky). For example, Columns (1) and (3) show that the price gradient in the overlapping and all nonprime markets differs by 3.4 bp ($=25.78-22.37$) per one one-pp increase in the predicted delinquency rate, while Columns (2) and (4) show that the differential price gradient in the prime markets is 28.4 bp ($=89.26-60.92$).

²²Panel (b) of Table A.1 in the Appendix reports statistics by the four segments: NO, PO, NA, PA. Across the four segments, interest rates vary from 11.17% for the PA loans, 15.45% for the PO loans, and 26.45% for the NO loans to 27.90% for the NA loans. The largest difference is 16.73% between the PA and NA loans, followed by 11% between the PO and NO loans. Loan amounts obtained by prime borrowers are generally higher than those obtained by nonprime borrowers. Loan sizes for NO are only 44% of those for PO.

4.2 Realized Return

Interest rate sensitivity to risk is very different for prime and nonprime borrowers. However, without examining ex-post performance, it is difficult to interpret which (if any) of these market segments appropriately prices risk. If rates are sufficiently sensitive to risk, we would expect realized returns to remain constant with risk or perhaps increase. In this subsection, we test this relationship for different market segments for matured loans only using loan-level IRRs, which summarizes the total cash flows during the loan term, net of actual losses.²³ The analysis may help address the concern that higher rates charged on nonprime loans, although not justifiable with the expected risk, may be justifiable with their higher loss severity.

Panel B of Table 7 reports the results. Similar to Panel A, Columns (1) and (2) are based on all nonprime and prime loans, respectively; Columns (3) and (4) are based on nonprime and prime loans in the overlapping region, respectively; Column (5) estimates a difference-in-differences (DID) specification based on all loans in the overlapping market. The negative and significant coefficients on predicted delinquency in all five columns indicate that IRR decreases with expected risk, suggesting that lenders generally do not price loans according to their expected risk. This is especially true for nonprime and prime loans in the overlapping market with coefficient being -105.86 and -95.10, respectively, both significant at the 1% level. The insignificant coefficient on the interaction term on predicted delinquency and the nonprime dummy suggests that the difference in the IRR-risk slope between nonprime and prime loans in the overlapping market is not statistically different from zero. In addition, Column (5) shows that nonprime loans are associated with an IRR of 12.53 pp higher than prime loans with similar risks.

To visually illustrate this result, we plot the average IRR against expected risk in Figure 6.

²³There are several important caveats to using this IRR. First, it is only available for matured loans, which limits the sample to loans originated before July 2017. Second, the particular economic scenario during our sample period is relatively benign and may not represent a full business cycle. Third, we do not observe origination fees, servicing fees, or the lender's cost of capital and debt used to finance the loans. Thus, we cannot make inferences about lenders' profitability.

It shows that nonprime loans deliver substantially higher returns, about 11.6% on average, in the overlapping region. Furthermore, in both segments, returns always decrease in risk, except for the safest loans in the prime alone segment shown in Column (6), which exhibit constant returns in risk. The pattern of decreasing returns is suggestive of inefficient pricing. Even worse, the most risky tails of both prime and nonprime segments show negative returns.

4.3 Summary

Put together, we find that pricing of FinTech loan is rather simplistic and inefficient based on three findings. First, nonprime loans are charged a 45% premium that is not justifiable with their underlying risk, including both default and prepayment risks, compared to prime loans with similar risk. Second, within each of the market segments, pricing of nonprime loans is less responsive to expected risk than that of prime loans, with its pricing-risk slope smaller by 56%. Third, loan-level returns generally decrease with expected risk for both prime and nonprime loans, suggesting that lenders realize excess returns from less risky loans in both segments while losing money on more risky ones. The patterns in FinTech pricing implies that there is a great deal of cross-subsidization on the online lending platforms, from nonprime to prime segments and, within each segment, from low-risk and high-risk loans. The distortion seems very persistent, with little change over time.

5 Implications of FinTech Pricing

What are the consequences of the seemingly simplistic and inefficient pricing of FinTech loans that we have documented? Clearly, FinTech platforms may be helping some borrowers obtain low rates at the expense of other borrowers. This section aims to quantify the effective transfers that occur due to mispricing. We begin this analysis by determining counterfactual rates for each loan and then quantify the average overpayment or underpayment by market segment.

5.1 Estimating Counterfactual Rates

In an ideal world, loan rates would reflect the risk in such a way that returns would be constant, if not increasing, with risk. Any attempt to identify this counterfactual rate is difficult from a practical standpoint for at least two main reasons. First, ascertaining the appropriate return on a portfolio of consumer loans is difficult without knowing the individual beta that translates expected risk into an expected rate. From the data, we have seen most loans do not achieve appropriate returns since their returns decrease with risk. Second, while we observe the performance of loans conditional on their transacted loan rates, it is difficult to know how risk or repayment behavior will change under new counterfactual rates. This can be particularly problematic when adverse selection or moral hazard exist.

To address these challenges, we look for loans that exhibit non-decreasing returns in risk in our sample. From Figure 6, most loans in the non-overlapping prime segment—the least risky loans with an expected delinquency rate between 0% and 4%—pay an interest rate from around 7.5% to nearly 14%. Yet, despite these differences, their ex-post IRRs are persistently constant at around 5%. This pattern is further confirmed by results in Column (6) of Table 7 Panel B where the coefficient on predicted delinquency using these loans (calibration sample) is not statistically significant, suggesting that they exhibit constant returns to risk. Given these facts, we assume that these prime loans show the most appropriate risk-based pricing based on our existing data and riskier loans should be priced such that they generate at least this rate. We apply the estimated relationship between interest rates and risk in this segment, found in Panel A of Table 7, Column (6), to estimate a counterfactual rate for the remaining loans in the prime segment as well as for all loans in the nonprime segment.

We make several important assumptions in this counterfactual exercise. The first is that all loans can be appropriately priced based on the risk-rate relationship among the safest prime loans. This assumption may be less realistic with extremely risky loans due to, for example, the interest rate caps placed by the state usury laws. But for most loans, we find no reason to believe that the relationship should change dramatically. Our second

assumption is that risk is not affected by the interest rate of the loan. This assumption would be violated if the counterfactual rate influenced the selection of borrowers or moral hazard behavior on their part. For most loans, the negative impact of adverse selection will be a non-issue because the counterfactual rates are lower than the actual rates, implying that the true counterfactual may be even lower. For loans with estimated counterfactual rates higher than their actual rates, our results from the RDD at FICO 660 show that higher rates probably affect delinquencies more than IRRs.

5.2 Magnitude of Rate Differentials

Based on the actual and counterfactual rates for individual loans, we calculate the rate differential as

$$\Delta \hat{r}_{it} = r_{it, actual} - r_{it, cfactual}. \quad (6)$$

$\Delta \hat{r}_{it}$ quantifies the degree to which the loan interest rate differs from the counterfactual. A positive number indicates overpayment, and a negative number indicates underpayment relative to the rate the borrower would have received.

Panel (a) of Figure 7 plots the average $\Delta \hat{r}_{it}$ over the predicted risk for prime and nonprime loans separately. The rate differentials for all prime and nonprime loans are -0.50 pp (discount) and 4.3 pp (premium), respectively, primarily decreasing in predicted risk from 12.3 pp to -4.6 pp among nonprime loans.²⁴ Over 83% of the nonprime loans—those with an expected delinquency rate between 6% and 20%—are overpaying. In particular, those in the overlapping nonprime segment—with an expected delinquency rate between 6% and 13%—overpay by about 8 pp, which is slightly higher than the estimated rate gap 7.33 pp in Section 3. In contrast, only 48% of prime loans have positive $\Delta \hat{r}_{it}$, and magnitudes of overpayment are very small. By construction, the average rate differential for most loans

²⁴Some of this insensitivity may be due to state usury laws that restrict the maximum rates on consumer loans. Figure A.4 in the Appendix shows that note rates on nonprime loans are mostly capped at 36%.

in the non-overlapping prime segment is close to zero. However, the riskier loans in the overlapping prime segment are underpaying by 1.1 pp.

We also calculate the implied transfer in dollars over the first year of the loan arising from mispricing by multiplying the loan amount by the calculated differential,

$$\widehat{Transfer}_{it} = \Delta \hat{r}_{it} \times LoanAmount_{it}. \quad (7)$$

Panel (b) of Figure 7 plots the density distribution of $\widehat{Transfer}_{it}$. On average (weighted by loan size), nonprime borrowers pay \$289 to the other market while nonprime borrowers receive \$151 from the other market, but both with wide dispersion.²⁵ If the loan is paid through maturity, the transfer amount would be roughly two times $\widehat{Transfer}_{it}$, i.e., \$578 and -\$302 for nonprime and prime loans, respectively. In particular, those in the overlapping nonprime segment overpay \$490 in the first year and \$980 through maturity per loan to other borrowers, while those in the overlapping prime segment receive \$109 in the first year and \$218 through maturity per loan above and beyond the risk-based pricing.

How big are these transfers? We can use two benchmarks. First, [Hurst et al. \(2016\)](#) estimate mispricing in the mortgage market due to the national pricing policy of the government-sponsored enterprises (GSEs) to be −\$580 (subsidy) for high-risk states to +\$780 (taxes) for low-risk states. Second, following the onset of COVID-19, the U.S. Congress authorized the \$2.2 trillion CARES Act, which provided one-time direct cash payments of \$1,200 to low-income individuals making up to \$75,000 and another \$500 per dependent. Our estimated average interest payment by nonprime borrowers of \$490 in one year, or \$980 over the loan term, is comparable in magnitude to mortgage market mispricing despite loan maturities that are 5–10 times shorter. Relative to the CARES Act, this average overpayment would represent roughly 82% of the subsidy.

²⁵Nonprime borrowers at the 75th percentile pay \$596 in transfers, while prime borrowers at the same percentile pays only \$174.

6 Conclusion

FinTech lenders pride themselves on using innovative data and superior statistical techniques to screen borrowers and price loans. One would expect that the rise of these new lenders would result in loans rates that reflect the riskiness of borrowers and loans.

Our results show that reality is still far from ideal. We discovered that borrowers' FICO scores are still the most important determinant of pricing after analyzing 2.3 million unsecured personal loans made by FinTech platforms. Importantly, other variables known to predict default are not adequately priced. Finally, we document that even in this market, there is a substantial interest rate gap of 7.33 pp between prime and nonprime loans with very similar risks after controlling for both credit and prepayment risks.

We highlight several institutional features of the market that are likely to contribute to the tight reliance of lenders on FICO scores. In particular, due to banking regulations, banks refrain from making nonprime loans. As a result, competition is lower in the nonprime segment of the market. Furthermore, the cost of the capital available to lending in the prime segment is significantly cheaper since banks rely on low-cost deposits.

Our results demonstrate that the hysteresis that exists in traditional lending markets persists in the digital age. While the current credit scoring system provides an imperfect proxy for default likelihood, even sophisticated lenders find it very hard to break away from the current framework and cannot implement true risk-based pricing using big data and advanced technologies. The continued overreliance on traditional credit scores for unsecured pricing has societal implications. Our results show that nonprime borrowers—especially those with low expected risk—cross-subsidize prime borrowers, especially those with high expected risk, leading to more expensive credit provision for underserved populations.

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Figure 1. Performance and Interest Rates, by FICO and Predicted Risk

This figure presents heat maps of the average interest rate (Panel (a)) and 12-month delinquency rate (Panel (b)) based on all loans in the sample. Loans are sorted by FICO score (x -axis; binned at five-point intervals), and by a measure of ex-ante delinquency (y -axis; binned at 0.5-point intervals). The delinquency risk measure is the out-of-sample prediction of 12-month delinquency rate based on observable characteristics at origination, excluding FICO score.

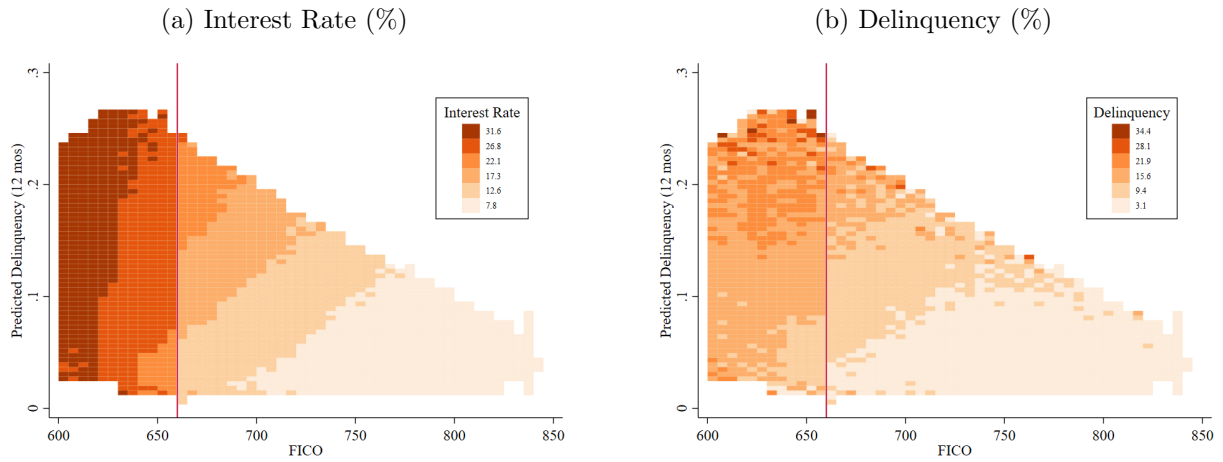


Figure 2. Discontinuities at the FICO 660 Cutoff

Plotted in the figures are coefficients and standard errors from ordinary least squares regressions for five-point FICO indicators. The dependent variable in Panel (a) is the interest rate on the loan. In Panel (b), the dependent variable indicates delinquency in the first 12 months. Lastly, in Panel (c), the dependent variable is the internal rate of return (IRR). In addition to FICO bins, the regressions include origination year-month fixed effects. All regressions are based on all loans in the sample. Standard errors are clustered by origination year-month.

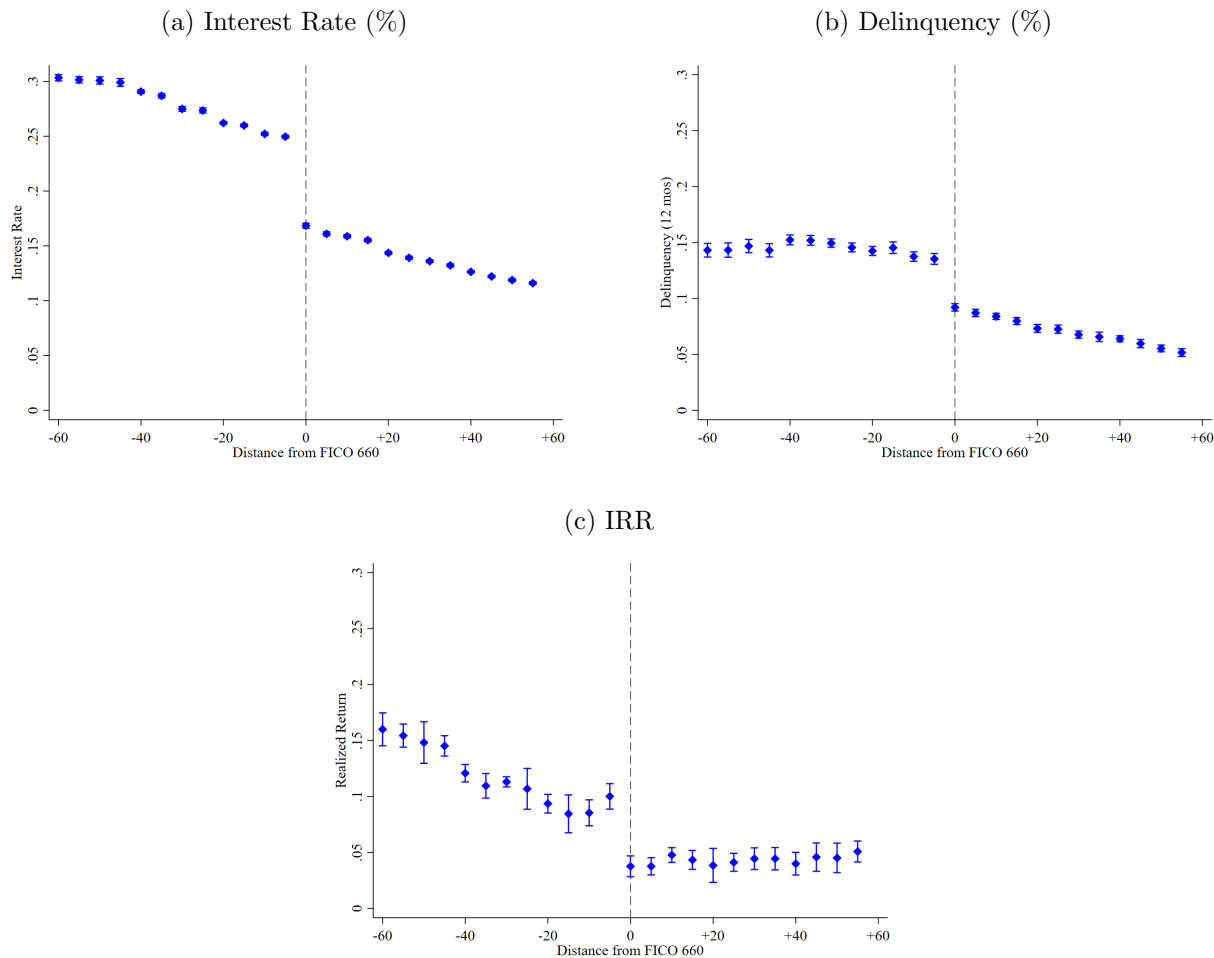


Figure 3. Credit Risk Model Coefficients over Time

This figure plots coefficients from rolling logit regressions used to predict the ex-ante probability of the loan becoming delinquent in the first 12 months for all loans originated from 2017 to 2020. The sample period for the regressions consists of 24 months of loan originations, with the most recent being 12 months before the prediction month. The dependent variable is an indicator that equals 1 if the loan became delinquent in the first 12 months. Select independent variables are plotted in two panels, with others shown in the Appendix, Figure A.3. Panel (a) shows the coefficients on 20-point FICO bin indicators, with the 640–659 FICO bin omitted. Panel (b) plots select coefficients from \$5,000 income bins, with \$55,000 as the omitted bin. Standard errors are clustered by origination month.

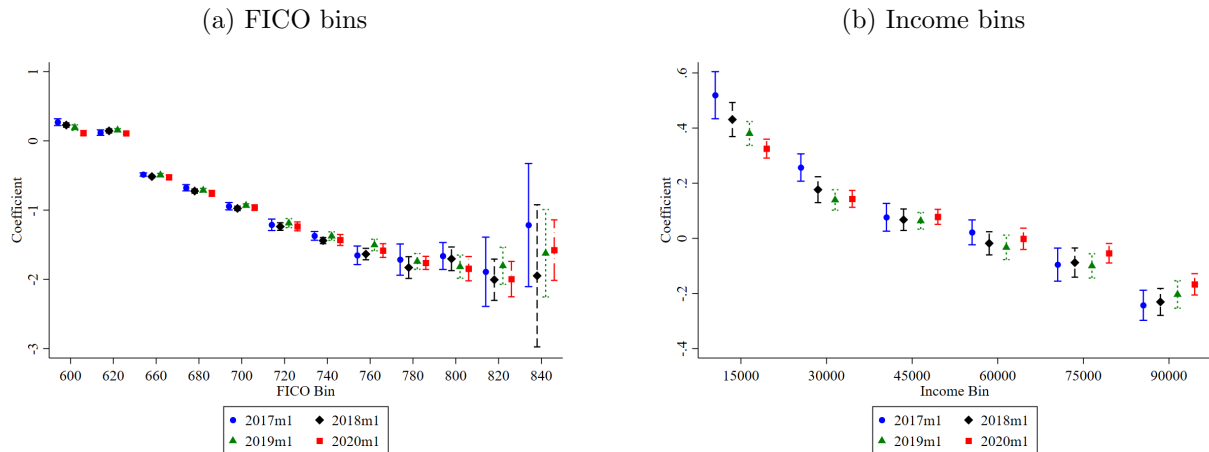


Figure 4. Performance of the Credit Risk Model

This figure compares the predicted loan performance relative to the actual performance for all loans in the sample, but separately for loans above and below FICO score 660. Predicted delinquency is estimated using rolling logit regressions from the prior three years of originations such that the prediction is out of sample. Panel (a) shows predicted delinquency relative to actual delinquency, with the overlapping region of risk between prime and nonprime highlighted in gray. Panel (b) shows the relationship between ex-ante risk and default for the subset of loans that have reached maturity. Default occurs when the loan is ultimately charged off by the lender.

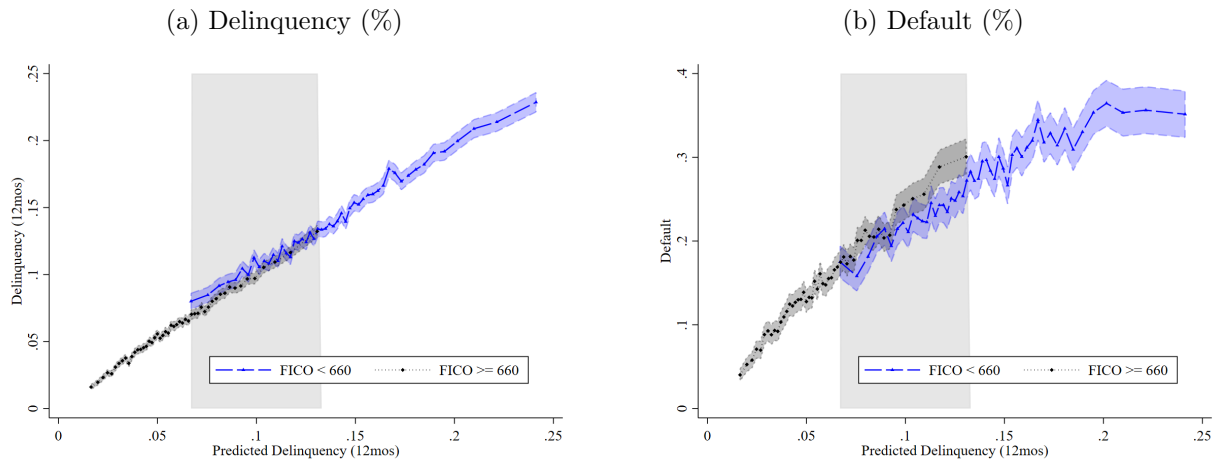


Figure 5. Ex-ante Predicted Risk and Rate

This figure shows the relationship between expected risk and pricing for prime and nonprime loans. Predicted delinquency is estimated using rolling logit regressions from the prior three years of originations such that the prediction is out of sample. Panel (a) plots the average interest rate and standard errors by expected risk separately for all prime and nonprime loans in the sample, with the overlapping region highlighted in gray. Panel (b) plots the loan rate difference between nonprime and prime loans in the overlapping region separately for 2017, 2018, and 2019.

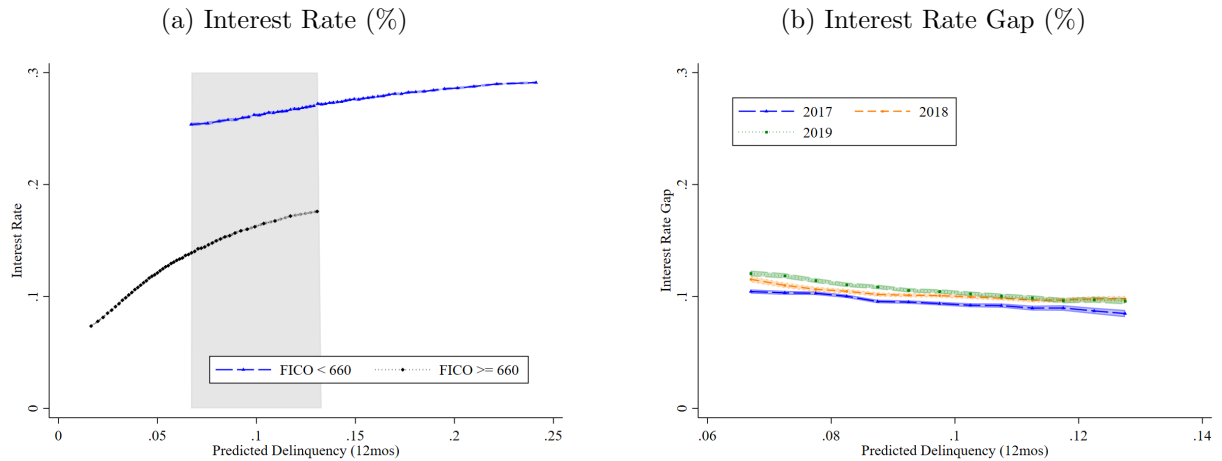


Figure 6. Ex-ante Predicted Risk and Realized IRR

This figure shows the relationship between realized loan-level IRR and predicted risk separately for all prime and nonprime loans in the sample. Plotted is the average IRR by predicted delinquency bins, along with standard errors. IRR is calculated using the initial outlay (loan amount) and subsequent cash flows (loan repayments) observed in the panel data. These cash flows also include loan recoveries when the loan is charged off. Only loans reached maturity as of July 2020 are included in this sample.

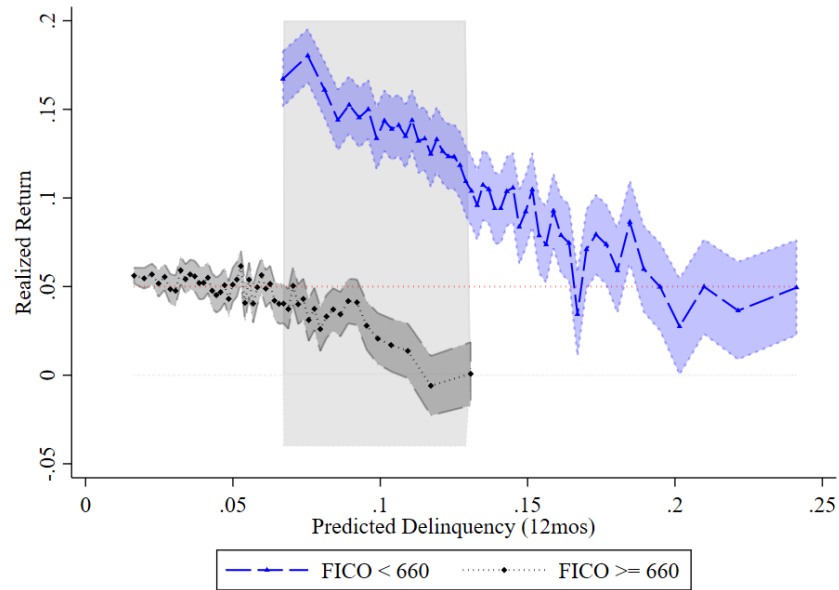


Figure 7. Magnitude and Distribution of Rate Differentials ($\Delta\hat{r}_{it}$)

This figure shows the distribution of rate differentials $\Delta\hat{r}_{it}$, defined as the difference between the actual rate and the calculated counterfactual rate for all prime and nonprime loans in the sample, respectively. The counterfactual interest rate is calculated using the coefficients from the pricing model of “safe” prime loans that exhibit ex-post constant returns in risk. Panel (a) shows the relationship between $\Delta\hat{r}_{it}$ and predicted risk. Panel (b) shows the distribution of $\Delta\hat{r}_{it}$ multiplied by the loan amount to demonstrate the dispersion in interest differentials in annual interest payments.

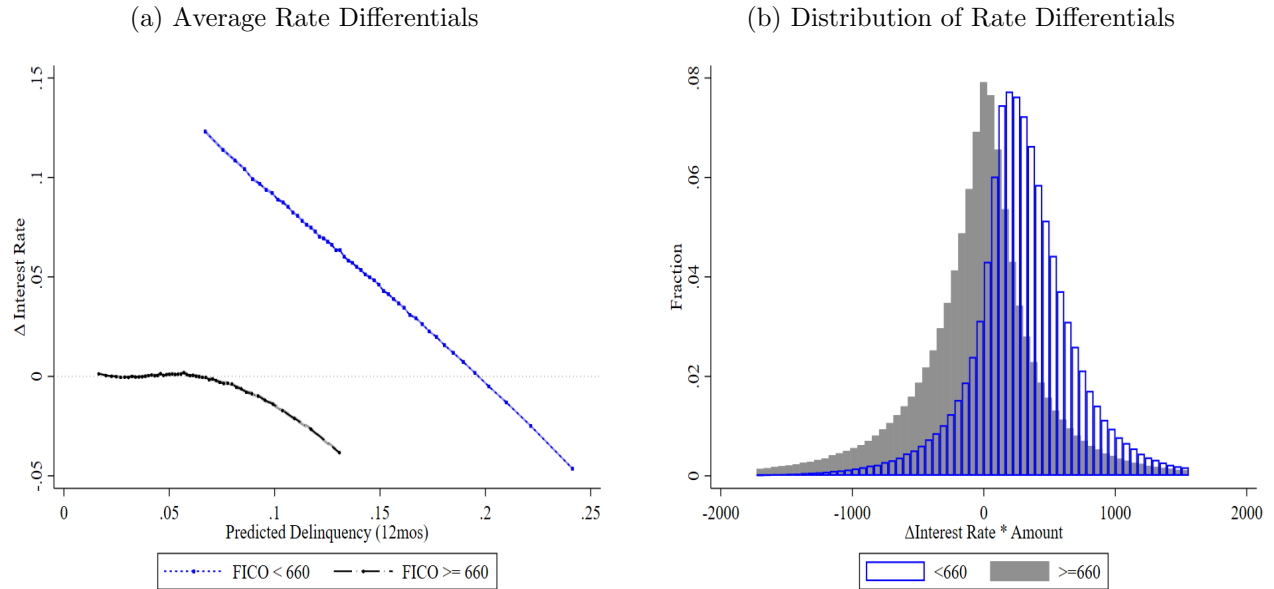


Table 1. Summary Statistics

This table presents summary statistics of borrower and loan characteristics. The data come from a FinTech loan aggregator specializing in FinTech lending. The sample is restricted to 36-month loans. *Rate (%)* is the annual interest rate. *Payment* is the monthly payment amount in dollars. *Age of Credit* is the age of their oldest credit found in the credit report. *No. of Inquiries* is the number of credit inquiries the borrower made as reported by the credit bureau in the 6 months before origination. *Credit Utilization* is the fraction of the borrower’s available revolving credit being utilized at the time of origination. *Default* occurs when a loan is charged off within its duration, and 12-month *Delinquency* occurs when the loan has a delinquent payment within one year since origination. *IRR* is the calculated internal rate of return using all cash flows at the loan level, excluding any financial or operating costs on the lender side.

	N	Mean	Median	SD	Min	Max
Interest Rate (%)	2,313,105	16.29	13.59	8.48	0.91	52.41
Loan Amount (\$)	2,313,105	11,898	10,000	8,386	500	44,500
Term	2,313,105	36.00	36.00	0.00	36.00	36.00
Payment	2,313,105	410	334	274	44	1235
FICO	2,313,105	684	677	44	600	850
Income	2,313,105	73,446	62,500	43,594	16,812	250,000
Payment/Income, annual %	2,313,105	0.07	0.07	0.04	0.01	0.21
Age of credit	2,313,105	194	175	92	41	483
No. of Inquiries	2,313,105	0.71	0.00	1.03	0.00	5.00
Credit Utilization	2,313,105	0.53	0.54	0.25	0.01	0.99
I(Loan Purpose: Debt Consolidation)	2,313,105	0.76	1.00	0.43	0.00	1.00
I(Loan Purpose: Home Improvement)	2,313,105	0.07	0.00	0.25	0.00	1.00
I(Homeowner)	2,313,105	0.55	1.00	0.50	0.00	1.00
Default (%)	2,313,105	14.44	0.00	35.15	0.00	100.00
Delinquency (%)	2,313,105	8.12	0.00	27.31	0.00	100.00
Pre-Payment (%)	2,313,105	45.85	0.00	49.83	0.00	1.00
IRR (%)	1,138,365	6.15	12.12	29.74	-100.00	41.80

Table 2. RDD Regression

This table estimates the difference in loan interest rates and delinquency for borrowers who fall just below the prime threshold of FICO 660. $I(FICO < 660)$ identifies borrowers with FICO scores below 660, and the coefficient represents the jump in loan rates for borrowers below the threshold. RDD controls include $FICO-660$ and its interaction with the indicator, which allow for the slopes to differ on either side of the threshold with respect to FICO. All coefficients are multiplied by 100 for ease of reporting. Columns (1) and (4) use a bandwidth of ± 40 FICO points; Columns (2) and (5) use ± 20 points; and Columns (3) and (6) use ± 5 points. All regressions include a control for the log of loan amount and fixed effects for the state, origination year-month, and state-by-year. Standard errors are clustered by origination month. *** indicates significance at the 1% level.

Dep Var	Interest Rate (%)			I(Delinquency)		
	(1)	(2)	(3)	(4)	(5)	(6)
I(FICO < 660)	8.57*** (0.12)	9.13*** (0.12)	9.43*** (0.12)	4.45*** (0.19)	4.53*** (0.23)	4.88*** (0.22)
Sample Restriction	620-699	640-679	655-664	620-699	640-679	655-664
RD Controls	Yes	Yes	No	Yes	Yes	No
Loan Attributes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Origination YM FE	Yes	Yes	Yes	Yes	Yes	Yes
State \times Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,457,316	822,252	213,017	1,457,316	822,252	213,017
R ²	0.55	0.49	0.64	0.02	0.02	0.13

Table 3. Rate Gap in the Overlapping Sample

This table shows estimates from ordinary least squares regressions of loan rates on nonprime dummy based on loans in the overlapping region, i.e., those with a predicted delinquency between 6% and 13%. $I(\widehat{Delinquency})$ is the predicted delinquency rate based on a real-time credit risk model specified in Equation (2). The sample includes loans with predicted delinquency between 6% and 13% where prime and nonprime loans are overlapped. The dependent variable is the loan interest rate. Specifications (1) and (3) include $I(\widehat{Delinquency})$ as a continuous variable, while specification (2) uses $I(\widehat{Delinquency})$ as a categorical variable, with groups at every .05% of predicted delinquency. Standard errors are clustered by origination year-month. *** indicates significance at the 1% level.

Dep Var	Interest Rate (%)		
	(1)	(2)	(3)
I(FICO < 660)	7.33*** (0.08)	7.16*** (0.07)	6.22*** (0.09)
$I(\widehat{Delinquency})$	71.37*** (1.19)		64.99*** (1.67)
Log(Loan Size)	-2.72*** (0.06)	-2.71*** (0.06)	-2.66*** (0.06)
$I(\widehat{Delinquency})$ Bin FE	No	Yes	No
Origination YM FE	Yes	Yes	Yes
Sample	All Loans	All Loans	FICO 640-680
N	848,552	848,552	512,484
R ²	0.57	0.57	0.44

Table 4. Prepayment Risk and Rates

This table shows estimates the effect of prepayment risk on rate differential between prime and nonprime loans based on loans in the overlapping region, i.e., those with a predicted delinquency between 6% and 13%. The dependent variable in Columns (1)-(3) is an indicator equal to 100 if the loan is paid off in full before maturity at 36 months. In Columns (4)-(6), the dependent variable is the loan interest rate. The primary independent variable is an indicator of nonprime status while controlling for predicted delinquency, loan size and predicted prepayment risk. All specifications include origination year-month fixed effects. Standard errors are clustered by origination year-month. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep var	I(Prepayment)			Interest Rate (%)		
	(1)	(2)	(3)	(4)	(5)	(6)
I(FICO < 660)	2.85*** (0.25)	2.94*** (0.27)	3.12*** (0.25)	7.33*** (0.08)	7.05*** (0.08)	6.22*** (0.09)
$I(\widehat{Delinquency})$	-58.08*** (7.34)	-59.16*** (7.53)	-59.47*** (8.58)	71.38*** (1.17)	72.93*** (1.13)	64.99*** (1.64)
Log(Loan Size)	-1.41*** (0.15)		-1.39*** (0.19)	-2.72*** (0.06)		-2.66*** (0.06)
$I(\widehat{Prepayment})$				0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Loan Size Bin FE	No	Yes	No	No	Yes	No
Origination YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All Loans	All Loans	FICO 640-680	All Loans	All Loans	FICO 640-680
N	848,552	848,552	512,484	848,552	848,552	512,484
R ²	0.13	0.13	0.13	0.57	0.58	0.44

Table 5. Performance of Nonprime Loans During COVID

This table estimates the impact of COVID-19 on delinquency in a difference-in-differences framework using loan panel data. The sample tracks the history of any loan outstanding as of October 2019 that are in the overlapping region from October 2019 through July 2020. The dependent variable is an indicator equal to 100 if the loan misses a payment in that month and 0 otherwise. The main explanatory variable, $I(<660) \times COVID$, is the interaction of the nonprime loan dummy with a post-COVID-19 dummy equal to 1 if the performance date is after February 2020. All regressions include a borrower and performance date fixed effects. Other specifications include state-by-month, predicted delinquency-by-month, and origination date-by-month fixed effects. Standard errors are clustered by performance date-by-state. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep Var	I(Delinquency) $_{i,t}$		
	(1)	(2)	(3)
$I(FICO_i < 660) \times I(COVID_t)$	-0.43* (0.24)	-2.08*** (0.30)	-2.24*** (0.20)
Borrower FE	Yes	Yes	Yes
Calendar Time FE	Yes	Yes	Yes
$\widehat{I(Delinquency)}_{i,0} \times \text{Calendar Time FE}$	No	Yes	Yes
State \times Calendar Time FE	No	No	Yes
Origination YM \times Calendar Time FE	No	No	Yes
N	5,182,793	5,182,793	5,182,793
R ²	0.32	0.32	0.52

Table 6. Hand-Collected Information on Lender’s Minimum FICO Rules

This table identifies the minimum FICO scores that banks and online lenders will consider in credit underwriting decisions for unsecured personal loans. The 15 largest banks by asset size are reported in bold, and other bank lenders with a significant presence in this credit market are included. For online lenders, the seven largest lenders by origination volume are in bold. These minimums are identified using personal finance websites (e.g., WalletHub or NerdWallet) when the data are unavailable through the institution’s own website. Data collection was performed in November 2021.

Min. FICO	580	600	620	640	660	680	700
Bank					Wells Fargo American Express SunTrust (LightStream) Discover Goldman Sachs (Marcus)	Citibank U.S. Bank Fifth Third Bank	TD Bank HSBC Barclays
Online Lender	Avant	Best Egg LendingClub LendingPoint Upstart	Freedom Plus Upgrade	Payoff Rocket Loans Prosper		SoFi	

Bold represents the largest banks (15) and largest FinTech lenders (7).

The following do not offer personal unsecured loans: Chase Bank, Bank of America, Capital One, Bank of New York Mellon, and State Street Bank.

Table 7. Relationship Between Interest Rates, Returns, and Predicted Risk

This table estimates the sensitivity of loan interest rates and returns to predicted risk for various samples. The dependent variable is the loan interest rate in Panel A and loan-level realized return in Panel B. The independent variable is the predicted delinquency from the credit risk model. Columns (1) and (2) use all nonprime and prime loans, respectively. Columns (3)–(5) use only loans in the overlapping region where prime and nonprime loans overlap in risk. Column (5) includes an indicator for nonprime loans and their interaction with predicted delinquency. Column (6) shows the calibration sample of safe prime loans used to determine counterfactual rates. In Panel B the sample is restricted to loans that have full performance data for the calculation of returns. Origination year-month fixed effects are included in all regressions. Standard errors are clustered by origination year-month. *** indicates significance at the 1% level.

Panel A: Interest Rate

Dep Var	Interest Rate (%)					
Sample	All		Overlap Region			Calibration
	Nonprime	Prime	Nonprime	Prime	Both	Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{I(Delinquency)}$	22.37***	89.36***	25.78***	60.92***	60.52***	116.63***
	(1.09)	(0.97)	(2.39)	(1.19)	(1.13)	(4.52)
$\times I(FICO < 660)$					-33.81***	
					(2.41)	
$I(FICO < 660)$					13.98***	
					(0.33)	
Origination YM FE	Yes	Yes	Yes	Yes	Yes	Yes
N	827,441	1,272,659	340,924	507,628	848,552	293,596
R ²	0.04	0.23	0.01	0.06	0.49	0.07

Panel B: Realized Return

Dep Var	Interest Rate (%)					
Sample	All		Overlap Region			Calibration
	Nonprime	Prime	Nonprime	Prime	Both	Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{I(Delinquency)}$	-105.79***	-57.81***	-105.86**	-95.10***	-95.31***	-7.28
	(6.56)	(5.33)	(15.48)	(8.78)	(8.76)	(9.69)
$\times I(FICO < 660)$					-9.97	
					(17.80)	
$I(FICO < 660)$					12.53**	
					(1.77)	
Origination YM FE	Yes	Yes	Yes	Yes	Yes	Yes
N	80,292	122,992	37,995	46,015	84,010	29,224
R ²	0.01	0.00	0.00	0.00	0.02	0.00

Appendix

Figure A.1. Interest Rates by FICO Based on an Alternative Sample

This figure plots the average loan interest rates by FICO score bins separately for the entire dataset (“All Loans”) and the sample that we use throughout the paper (“Filtered Sample”). See subsection 2.2 for a full description of the construction of the filtered sample. *Interest Rate* is the interest rate charged on the loan and does not include origination fees in the filtered sample but may include fees in the “all loans” sample. FICO scores are binned at intervals of five points.

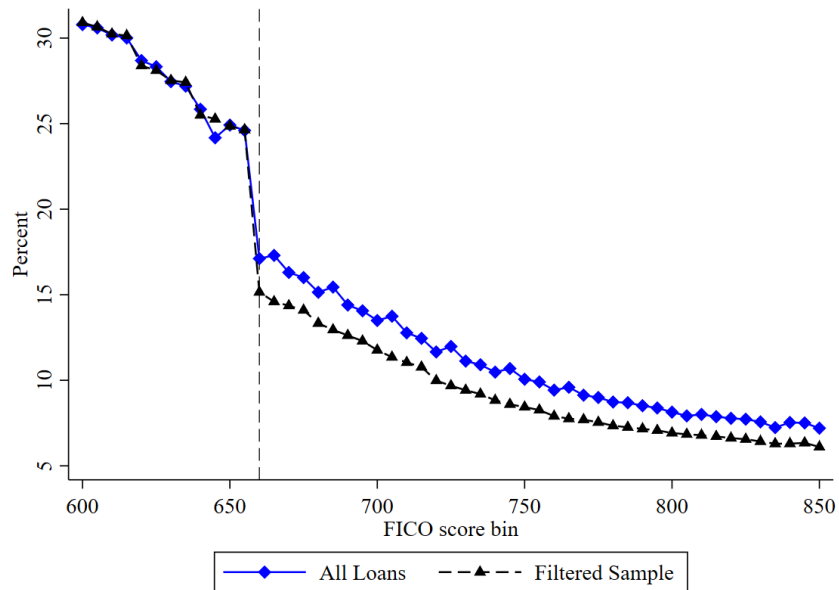


Figure A.2. More RDD Regressions

This figure shows the discontinuity at FICO 660 for loan characteristics and the monthly income of the borrowers. The dependent variables are loan size in Panel (a), borrower income in Panel (b), and monthly payment in Panel (c). For each panel, the corresponding dependent variable is regressed on FICO score bins, controlling for originating month fixed effects. All regressions are based on all loans in the sample. Standard errors are clustered at the monthly level. The coefficients are plotted on credit score bins, along with the confidence intervals at the 95% level.

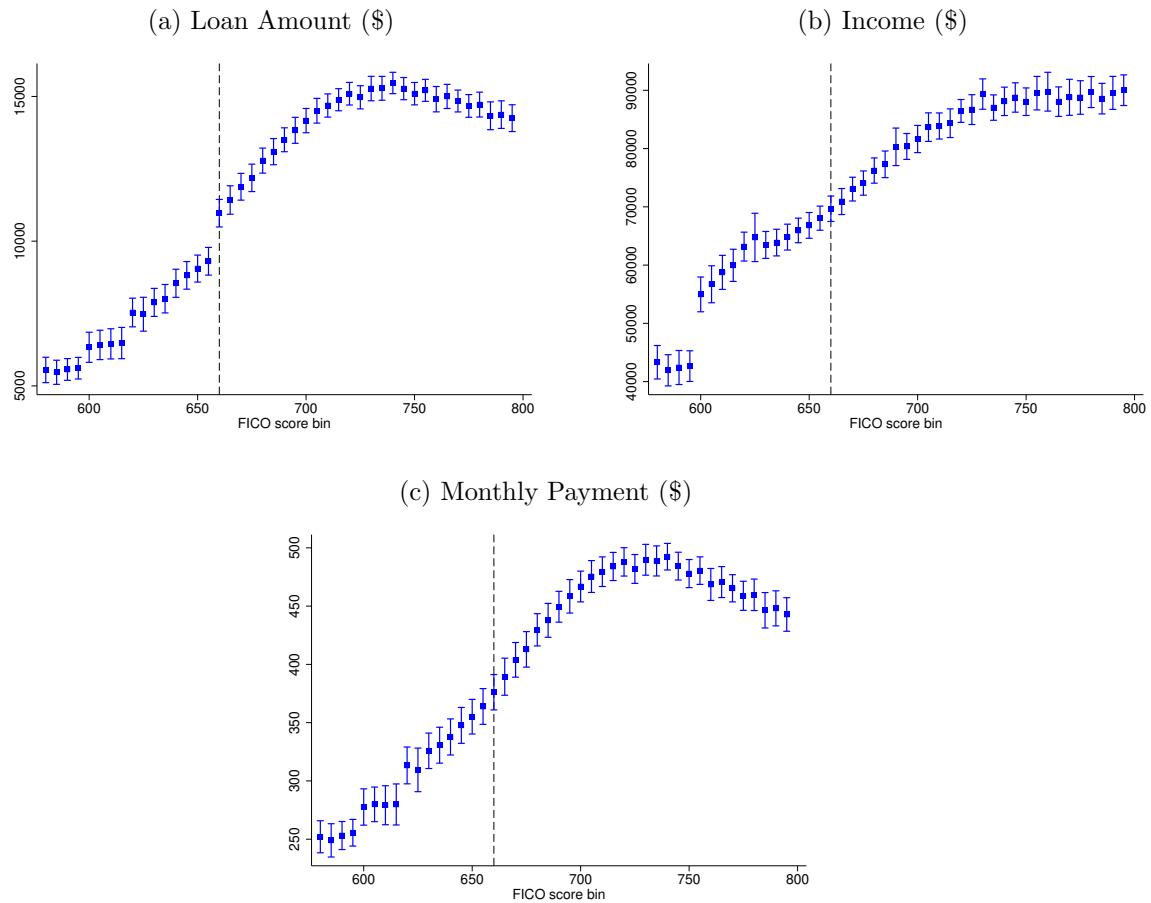


Figure A.3. More Credit Risk Model Coefficients over Time (Figure 3 Continued)

This figure plots other coefficients from logit rolling regressions used to predict the ex-ante delinquency risk. The estimation sample consists of 24 months of loan originations, with the most recent being 12 months before the prediction month. The dependent variable is an indicator equal to 1 if the loan became delinquent in the first 12 months. Panel (a) plots select coefficients for \$1,000 loan amount bins, with the \$10,000 bin omitted. Panel (b) plots coefficients for other credit bureau information as well as indicators for the largest reported loan purposes—credit card refinancing, home improvement, and medical—with debt consolidation as the omitted category. $\Delta FICO$ is the borrower's FICO score minus the midpoint of their 20-point FICO bin. $Cr. Age$ is the age of their oldest credit found in the credit report. $\# Inq.$ is the number of credit inquiries the borrower made in the 6 months prior to origination. $Cr. Util.$ is the ratio of the borrower's revolving credit utilization at the time of origination. Standard errors are clustered by origination month.

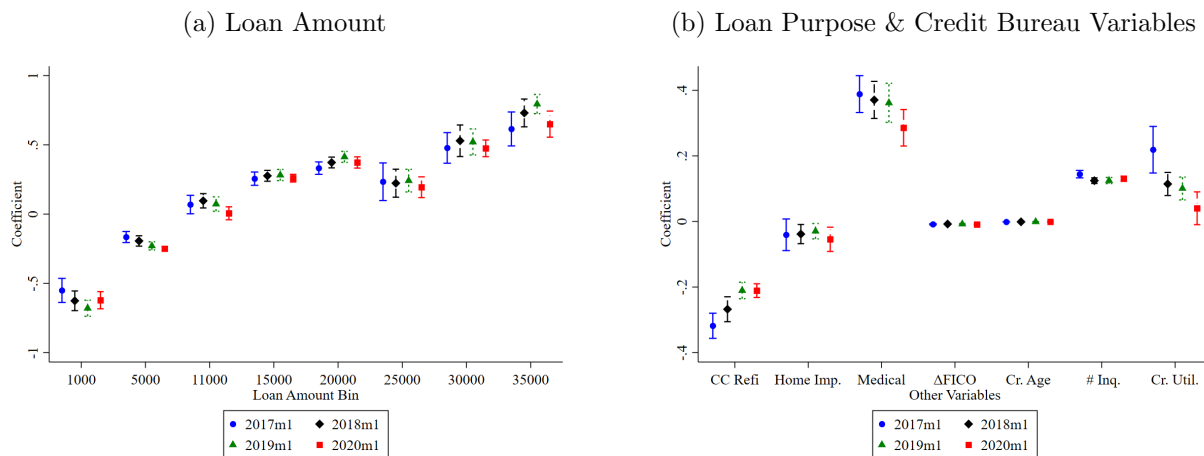


Figure A.4. Distribution of Interest Rates by Market Segments

This figure shows the distribution of interest rates separately for prime and nonprime loans.

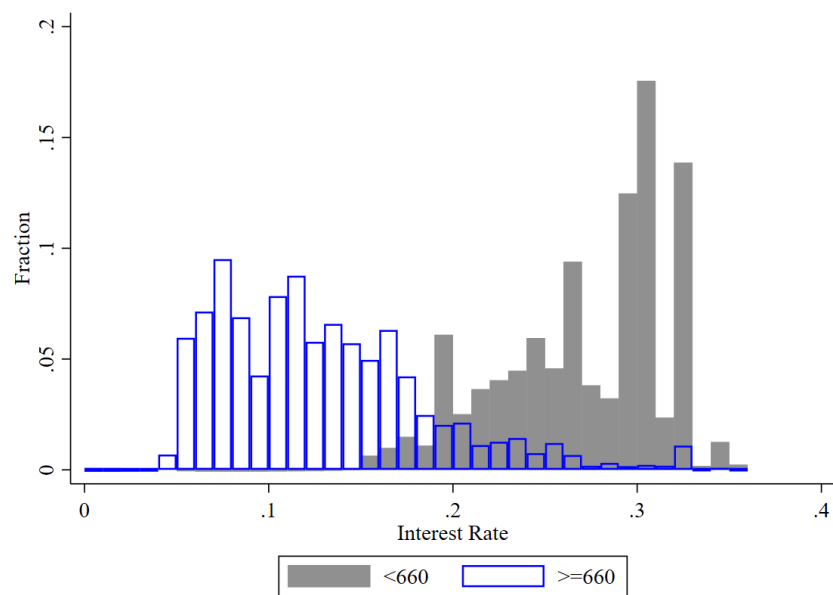


Table A.1. Additional Summary Statistics

This table presents summary statistics of borrower and loan characteristics. Panel (a) reports summary statistics of the loan panel used in Section 3.4. The sample tracks the history of any loan outstanding as of October 2019 that are in the overlapping region from October 2019 through July 2020. The subsample is further divided into before and during/post-COVID periods. Panel (b) reports statistics on all loans. The sample is divided into four segments: non-overlapping prime, overlapping prime, overlapping nonprime and non-overlapping nonprime. Overlapping prime and overlapping nonprime loans make up the overlapping region/sample.

Panel A: Loan by Month Panel Sample

	Overlapping Prime				Overlapping Nonprime			
	Pre-COVID		Post-COVID		Pre-COVID		Post-COVID	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
$I(\text{Delinquency})_{i,t}$ (%)	10.18	30.24	12.67	33.26	11.56	31.98	12.90	33.52
$\text{Rate}_{i,0}$	15.04	5.65	14.98	5.64	26.32	4.79	26.29	4.80
$\text{Loan Amount}_{i,0}$	12,265	7,597	12,374	7,623	5,150	3,202	5,135	3,191
FICO_0	681.43	17.37	681.76	17.50	637.91	14.98	637.75	15.09
$\widehat{I(\text{Delinquency})}_{i,0}$	8.81	1.58	8.81	1.59	10.90	1.54	10.90	1.54
N	1,922,547		1,205,912		1,277,572		776,962	

Panel B: Individual Loan Sample by Subsamples

	Non-overlapping Prime		Overlapping Prime		Overlapping Nonprime		Non-overlapping Nonprime	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Rate (%)	11.17	4.96	15.45	5.70	26.45	4.70	27.90	4.43
Loan Amount (\\$)	9,479	6,788	12,102	7,583	5,344	3,345	7,868	4,382
Term	36.00	0.00	36.00	0.00	36.00	0.00	36.00	0.00
Payment	307	215	417	253	216	133	324	179
FICO	719	37	680	17	638	15	633	15
Income	58,408	20,318	53,443	20,218	54,035	19,819	47,621	19,318
Payment/Income	0.07	0.04	0.10	0.05	0.05	0.03	0.09	0.04
Age of credit	200	98	165	82	181	87	149	73
No of Inquiries	0.43	0.74	0.82	1.12	0.57	0.85	1.18	1.35
Credit Utilization	0.40	0.24	0.53	0.23	0.63	0.25	0.65	0.24
$I(\text{Debt Consolidation})$	0.76	0.43	0.76	0.42	0.68	0.47	0.66	0.48
$I(\text{Home Improvement})$	0.07	0.25	0.04	0.20	0.07	0.25	0.05	0.21
$I(\text{Homeowner})$	0.56	0.50	0.47	0.50	0.45	0.50	0.42	0.49
$I(\text{Default})$ (%)	7.54	26.41	14.05	34.75	15.89	36.56	22.68	41.88
$I(\text{Delinquency})$ (%)	4.60	20.95	8.98	28.59	11.36	31.73	16.57	37.18
$I(\text{Prepayment})$ (%)	41.41	49.26	35.52	47.86	39.02	48.78	34.27	47.46
Prepayment Month	15.09	9.17	14.89	9.11	13.94	9.11	13.57	8.83
IRR (%)	5.10	22.95	3.11	31.64	8.19	42.49	13.62	36.71
N	765,031		507,628		340,924		486,517	